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Comparative Study of Optimization Models for Evaluation of EDM Process Parameters on Ti-6Al-4V

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Abstract: In this paper, different optimization techniques such as multi-objective optimization based on ratio analysis, the -nD angle, information divergence and multi-angle optimization methods were considered for comparative study in order to check their variation in results. These four techniques were considered asthese techniques were made from completely different methodologies, such as MOORA, is one of the latest multi-criteria decision-making methods that cover the weakness of other older methods and the latter three (-nD angle, Information Divergence and MAOT) methods are based on trigonometric methodologies. These optimization techniques were carried out using the effect of EDM process parameters viz., material removal rate and surface roughness as output parameters and current, pulse on time, pulse off time and different electrode materials as input process parameters. These parameters were obtained from the experiments modelled according to the Taguchi experimental design procedure in which the L_{18} orthogonal array was used to perform experimentation with the material of titanium alloy (Ti-6Al-4V). All the optimization techniques have obtained similar results among which -nD angle and Information Divergence technique tend to be easier and understandable for any similar application. The latter two methods avoid complexity and can be used for optimizing any relevant manufacturing process parameters such as the parameters of EDM, additive manufacturing, etc.

Keywords: EDM; information divergence; MOORA; -nD angle; orthogonal array; taguchi

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1. Introduction

Decision-making is an important task in almost every field of engineering when there are multiple factors involved. For instance, in the manufacturing field, in the Electrical Discharge Machining (EDM), the input process parameters affect the output parameters. In this process, the input process parameters are current (Amps), pulse-on (µs), pulse-off (µs) and flushing pressure (bar), etc., whereas output parameters could be material removal rate, electrode wear rate, radial overcut, etc. The input process parameters must be optimized in order to obtain the optimum output values [1–3]. Furthermore, when pursuing advances in computing systems, optimization techniques have become increasingly popular and important in different engineering applications [4].

In this study, three new simple techniques were introduced by comparing their results with the MOORA method. The output process parameters of the EDM were considered to optimize and find the suitable input process parameters for future machining procedures [5]. The EDM process follows a non-conventional machining procedure that removes the material from the substrate without being in physical contact with it. It is based on thermal energy by conversion from electrical energy which removes material by innumerable sparks between the tool electrode and the workpiece. Here, in straight polarity, the electrode acts as an anode and the workpiece act as a cathode, which develops the potential difference when they are close to each other to permit plasma channel creation between them. The thermal energy created due to potential difference leads to intense heat conditions on the workpiece causing melting and vaporizing of workpiece material. In this process, not just the workpiece is melted, but also sometimes there will be melting of an electrode which is measured with time as electrode wear rate (EWR) [6]. This change is the removal of the workpiece to electrode, which happens due to variation in process parameters, so it is important to optimize the parameters in order to machine further. Apart from the EWR, the process parameters will also cause uneven surface roughness which was considered in this study to find optimum parameters giving minimum surface roughness (SR) [7] with maximum material removal rate (MRR [8–10]). The EDM machine has various applications in various fields, so its parameters were considered to implement these techniques.

The input parameters that can be adjusted to obtain better output are current (Amps), pulse-on (µs), pulse-off (µs), and flushing pressure (Bar). Moreover, another parameter considered here was different electrode materials, i.e., brass, bronze, and copper, which could be optimized to find the better electrode for machining the workpiece of Ti-6Al-4V [11,12]. The experiments to be carried out were designed with the Design of Experiments (DOE) Taguchi experimental technique of L_{18} orthogonal array. This technique has been used in different fields for designing several experiments that have many factors to be considered. Due to the rapid development and increase in consumption of needs by individuals, industrial wastewater generation has increased abnormally [13]. There are various types of industrial wastewaters that are harmful to humans and the environment which is hard to manage the treatment process [14]. Recently, in the olive mill wastewater treatment process to validate the optimal operating conditions, gray relational analysis (GRA) was adopted [15], especially for coagulant dosage. Several researchers have developed different models to increase process efficiency and practical process assessment. The computational fluid dynamics model (CFD) was developed to analyze the distributions of radiation and chemicals through an in-flow reactor for the removal of recalcitrant organics in reverse osmosis concentrate from the coal chemical industry by UV/H_2O_2 and UV/PDS [16]. In another study, L.M.L.K.B. Lindamulla et al. [17] worked on an integrated mathematical model to simulate the performance of a membrane bioreactor and achieved calibration and validation of a model which enables the prediction of the system performance and membrane fouling under different operating conditions. Vuppala et al. [18] worked on olive mill wastewater treatment and proved the efficiency of the process through experimental and modeling by adapting the different pseudo-nth order models, identifying for each process step the most suitable one. This study would resolve the wastewater treatment optimization process by identifying the priorities based on multiple contradictory criteria towards a better sustainable approach that reduces CAPEX and OPEX of industries.

Here, three simple techniques (-nD angle, Information Divergence, and Multi-Angle Optimization Technique (MAOT)) are introduced to check the results in comparison with Multi-Objective Optimization of the Ratio Analysis (MOORA). The EDM output parameters were obtained by machining titanium alloy (Ti-6Al-4V) using three different electrodes [19–21].

2. Materials and Methods

In this work, Ti-6Al-4V alloy was used as workpiece material which has an extraordinary mechanical and thermal characteristic with outstanding resistance to corrosion, and a high strength-to-weight ratio. As it is known that traditional machining results in higher tooling costs, we use EDM, which is non-traditional machining is used to machine the material considering the economic constraints as shown in Figure 1 [22–24]. The low thermal conductivity, chemical composition, and the physical and mechanical properties [19] of the workpiece are given below in Table 1.

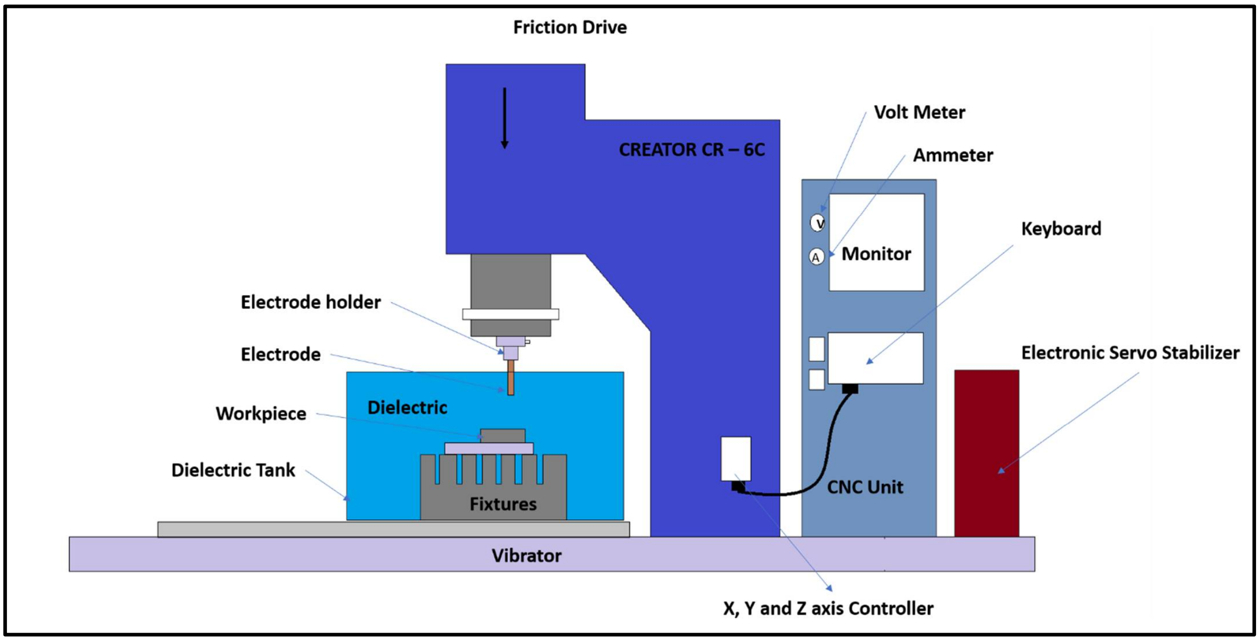

Figure 1. Computer numerical control die-sinking EDM.

Table 1. Ti-6Al-4V Chemical composition.

Element	Titanium	Aluminium	Vanadium	Iron	Oxygen	Carbon	Nitrogen	Hydrogen	Ref
Weight%	89.464–90	5.5–6.75	3–4.5	<0.3	<0.2	<0.1	<0.05	<0.015	[19]

Ti-6Al-4V (material) was supplied by Jay Steel Corporation Mumbai India. Dimension of 20 mm $\times$ 20 mm $\times$ 8 mm was considered for the substrate with the help of an abrasive cutting tool machine. Then, the work pieces were surface ground and cleaned with acetone for removing the build-up edges. Polishing with grit sizes of 400, 800, and 1200 was performed in both manual and automatic modes using emery papers and then cleaned up with acetone. Workpiece and tool are directly connected to DC power supply in which positive and negative terminals are workpiece and tool, respectively, or otherwise as straight polarity [25]. The constant gap between the tool and workpiece are given by the servo feed mechanism. The layer formation due to dielectric fluid between tool and workpiece are driven for spark with a break in the circuit [26]. Electrodes made of copper, bronze, and brass materials were used in the present process of machining with the size of 12 mm diameter and 100 mm length. Prior to the ED machining process, electrodes were taken for facing operation on the lathe.

2.1. -nD Angle and Information Divergence Method

-nD angle and Information Divergence [27]. This method was introduced to check whether this gives similar results as the optimization technique MOORA method.

Given the test vector t and a reference vector r of length C, the score a is calculated as given [28] in Equation (1):

$$a = \cos^{-1}\left[\frac{\sum_{i=1}^{C} t_i \gamma_i}{\sqrt{\sum_{1=1}^{N} t_i^2}\sqrt{\sum_{i=1}^{N} \gamma_i^2}}\right] \tag{1}$$

where t = test vector, a = reference vector, r = length, and C = score.

The Information Divergence (ID) method computes similarity based on the divergence between the probability distributions of the two vectors. Let t and r be test and reference vectors, respectively. Calculate the distribution values for the reference vector as given in Equation (2):

$$q_i = \frac{\gamma_i}{\sum_{i=1}^{c} \gamma_i} \tag{2}$$

where t = test vector and r = reference vector.

Calculate the distribution value for the test vector is given in Equation (3):

$$P_i = \frac{t_i}{\sum_{i=1}^{N} t_i} \tag{3}$$

Then, compute the ID value by using the probability distributions of the test and the references vectors as given in Equation (4):

$$\sum_{i=1}^{c} p_i \log\left(\frac{p_i}{q_i}\right) + \sum_{i=1}^{c} q_i \log\left(\frac{q_i}{p_i}\right) \tag{4}$$

where p_i = test vector data; q_i = reference vector data. Then, the combination of both techniques is termed as MAOT which is described below.

2.2. Multi-Angle Optimization Technique (MAOT)

MAOT deals with two angles as per its naming, and in remote sensing it has also been used for pixel classification [27]. This is the multiplication of information divergence value with the sin of -nD angle as represented in Equation (5).

$$\text{MAOT} = \text{ID} \times \text{Sin (-nD angle)} \tag{5}$$

This technique is more efficient than the two techniques as an individual because the -nD angle considers geometric features between two sequences, whereas ID considers two sequences as random and finds the probability values.

2.3. MOORA Methodology

MOORA stands for Multi-Objective Optimization based on Ratio Analysis which optimizes the two or more contradictory attributes simultaneously

Here, some criteria may be maximized and others may be minimized according to the requirement, but it considers both maximization and minimization principles for the selection of desired alternatives among all alternatives [29–31]. The steps for the optimization are as follows.

The first step is to develop a decision matrix showing the pertinent evaluation attributes for different alternatives:

$$X = \begin{vmatrix} X_{11} & X_{12} \ldots\ldots & X_{1b} \\ X_{21} & X_{22} \ldots\ldots & X_{2b} \\ X_{a1} & X_{a2} & X_{ab} \end{vmatrix} \tag{6}$$

Here, x_{ij} is the performance measure of i^{th} alternative in j^{th} criterion, wherein "a" is a number of alternatives and "b" is a number of criteria. The second step is the normalization of the decision matrix which is proposed as a ratio system to calculate the normalized performance as shown in Equation (7).

$$X_{ij}^{*} = X_{ij} / \sqrt{\sum_{i=1}^{a} x_{ij}^{2}} \tag{7}$$

Here, X_{ij}^{*} lies in [0, 1] and represents the normalized performance. The third step is the calculation of the overall performance as per Equation (7).

$$yA = \sum_{J=1}^{k} X_{ij}^{*} - \sum_{J=k+1}^{b} X_{ij}^{*} \tag{8}$$

Here, "k" is the number of parameters that need to be maximized and "b–k" is the number of parameters that need to be minimized. "yA" is the assessment value of i^{th} alternative concerning all the parameters. In many situations, it is witnessed that certain output parameters are more essential than the other parameters. In such situations, to provide more importance to certain parameters, individual weightage value needs to be multiplied. By considering the weightage value, Equation (8) can be modified as per Equation (9).

$$yA = \sum_{j=1}^{k} Wj \times X_{ij}^{*} - \sum_{j=k+1}^{b} Wj \times X_{ij}^{*} \tag{9}$$

Subjected to

$$\sum_{j=1}^{n} w_j = 1 \tag{10}$$

Here, Wj is the weightage value of output parameters. The value of "yA" can be positive or negative. The ranking of the yA value helps in assigning a sequence of preference of experiments. In other words, the highest value of yA can be considered as the best sequence of operation and vice versa.

3. Experimental Procedure

These experiments were conducted to study machining parameters with respect to their effect on EDM [32]. Here, four input parameters were considered for conducting the experiments: current (Amps), pulse on time (µs), pulse off time (µs), flushing pressure (bar), and different electrode materials (copper, bronze, and brass). The experiments were conducted based on Taguchi L_{18} orthogonal array which suggests to conducts 18 experiments. The experiments were carried out on the material of Titanium Alloy (Ti-6Al-4V) which has its application in various fields such as aerospace, biomedical, wastewater treatment plants, automobiles, etc., Here, it was used to demonstrate the new optimization techniques in the field of machining. Minitab 17 software was used to design the number of experiments [33]. The combination of parameters is shown in Table 2.

The output parameters considered in this study are material removal rate (*MRR*) and surface roughness (SR) [34]. Material removal rate can be defined as the relation of difference in material weight before and after the machining to the time taken for the machining process which is represented in Equation (1).

$$MRR = \frac{WBM - WAM}{Time} \tag{11}$$

Here, *WBM* = Weight before machining and *WAM* = Weight after machining.

A surface roughness tester was used to measure the surface roughness of the substrate. A Surftester (Model: SJ301, Make: Mitutoyo), as shown in Figure 2, was used to evaluate the surface of the machined specimens, and it provides the surface profiles of the surface. The tester compares the surface with respect to the plane typical to that surface, ordinarily, at right angles, and a measure of surface peaks and valleys was taken for optimizing the output parameters in order to find the optimum sequence of input parameters. Therefore, material removal rate and surface roughness are considered following the criteria of higher-the-better and lower-the-better, respectively [3,35]. The real profile is the profile obtained concerning the convergence of the workpiece surface and a plane typical to that surface. A path that increases the surface roughness value, ordinarily at right angles to the lay of the machining marks.

Table 2. Experimental layout using L_{18} orthogonal array.

Run	Current (Amps)	Ton (µs)	Toff (µs)	Flushing Pressure (bar)	Electrodes
1	10	200	40	0	Copper-1
2	10	400	80	0.5	Bromnze-1
3	10	600	120	1	Brass-1
4	20	200	40	0.5	Bronze-2
5	20	400	80	1	Brass -2
6	20	600	120	0	Copper-2
7	30	200	40	0	Brass-3
8	30	400	80	0.5	Copper-3
9	30	600	120	1	Bronze-3
10	10	200	40	1	Bronze-4
11	10	400	80	0	Brass-4
12	10	600	120	0.5	Copper-4
13	20	200	40	1	Copper-5
14	20	400	80	0	Bronze-5
15	20	600	120	0.5	Brass-5
16	30	200	40	0.5	Brass-6
17	30	400	80	1	Copper-6
18	30	600	120	0	Bronze-6

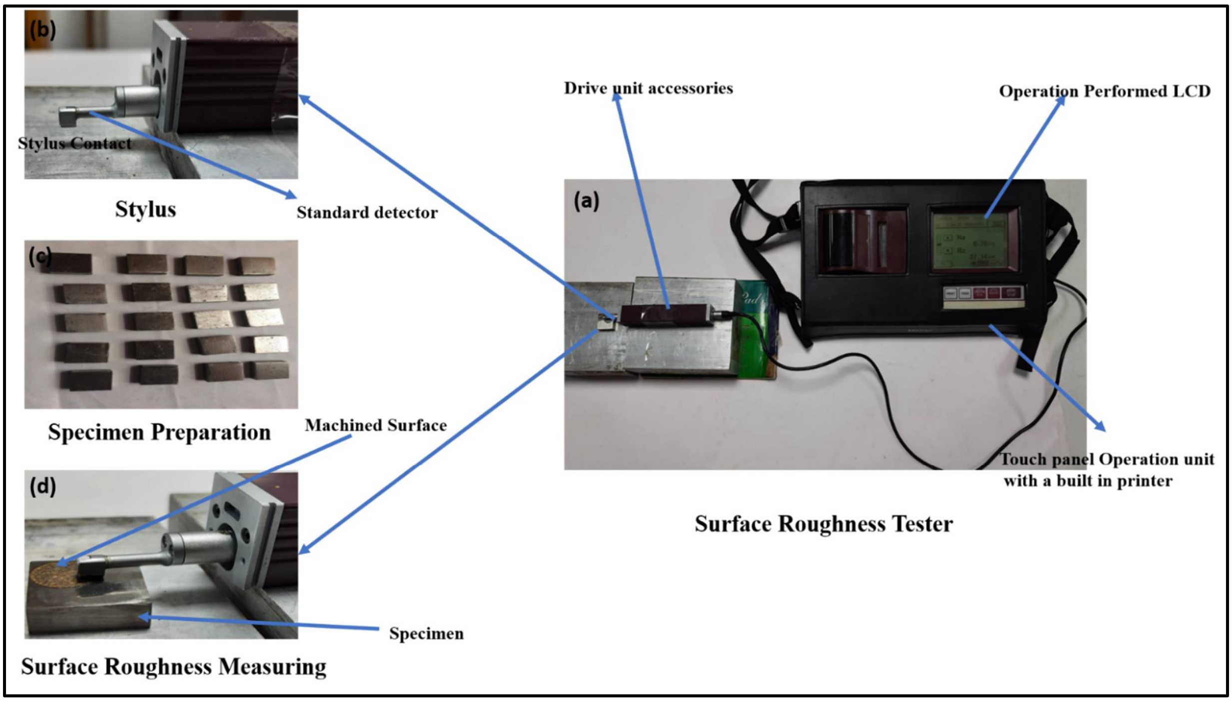

Figure 2. Experimental setup of surface roughness: (**a**) Surface roughness tester. (**b**) Stylus. (**c**) Specimen preparation. (**d**) Surface roughness measuring.

Surface flaws, like breaks, scratches, and marks, are not part of the profile and should not be remembered for the chronicle. In that event, essential resiliences as per DIN EN ISO 8785 can be set for them. The essential profile (R-profile) is the profile that results because of electronic low-pass sifting of the deliberate profile with a remove frequency λs. This process eliminates the shortest wavelength components that are specified not relevant to a roughness measurement.

Figure 3 shows the surface roughness measurements, i.e., surface roughness readings related to experiments 1, 4, and 9, which indicate roughness interpretations of maximum, medium, and minimum, respectively. Maximum roughness depth Rz1max for surfaces in which individual deviations have a significant influence on the function of the surface. Mean roughness depth Rz as a rule for all other surfaces. The arithmetical mean roughness value Ra is hardly affected by individual peaks or valleys because it is the mean value of the whole profile. It is, therefore, only of minor importance. In addition, the measuring point pitch Δx and the cut-off wavelength λ s of the low-pass filter are standardized. These values are, however, preset in roughness measurement devices.

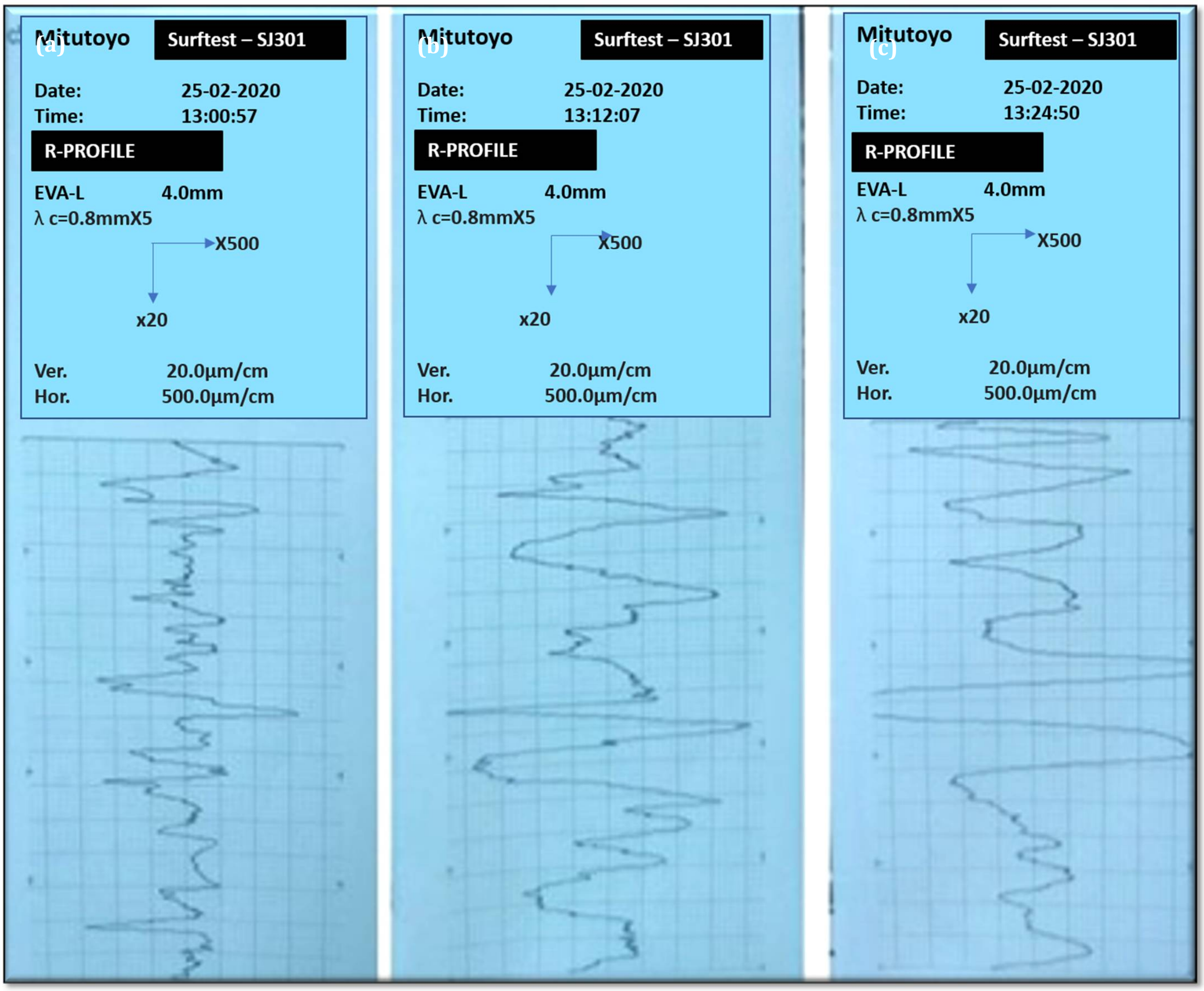

Figure 3. Surface roughness profile graphs: Experiment 1 (**a**). Experiment 4 (**b**). Experiment 9 (**c**).

4. Results and Discussions

Surface roughness (Ra) is the output parameter, which is not directly considered in this study, but desired values of input parameters are fixed with respect to the surface roughness. For example, in the case of surface roughness, the requirement is to obtain a lower surface roughness value. Therefore, from the literature, it was understood that for obtaining the lower value of surface roughness, it is better to have lower current, lower pulse on time, lower pulse off time, and lower flushing pressure. However, according to the design of experiments, it is not possible to select a suitable combination of parameters. Therefore, there is a requirement of optimization techniques to find a suitable combination of parameters for obtaining a lesser value of surface roughness. Table 3 shows the MRR and surface roughness values obtained for all the experiments in which a minimum of 0.19639 mm^3/min and 3.8825 µm and a maximum of 3.65237 mm^3/min and 11.61 µm and the maximum are obtained for the experiments number 3 MRR and 8 SR for minimum and 13 MRR and 9 SR (Ra) for maximum, respectively.

Table 3. Experimental data of MRR and SR.

Input Parameters						Output Parameters	
Experiments	**Current (Amps)**	**Ton (μs)**	**Toff (μs)**	**Flushing Pressure (bar)**	**Electrodes**	**MRR (mm^3/min)**	**Ra (μm)**
1	10	200	40	0	Copper-1	1.16479	4.95
2	10	400	80	0.5	Bromnze-1	0.96614	9.13
3	10	600	120	1	Brass-1	0.19639	6.545
4	20	200	40	0.5	Bronze-2	3.2754	6.805
5	20	400	80	1	Brass-2	0.23928	11.02
6	20	600	120	0	Copper-2	0.79233	6.9325
7	30	200	40	0	Brass-3	0.62077	4.4675
8	30	400	80	0.5	Copper-3	1.50113	3.8825
9	30	600	120	1	Bronze-3	1.81242	11.61
10	10	200	40	1	Bronze-4	1.41761	7.015
11	10	400	80	0	Brass-4	0.82299	7.5125
12	10	600	120	0.5	Copper-4	0.40406	11.32
13	20	200	40	1	Copper-5	3.65237	6.02
14	20	400	80	0	Bronze-5	2.47404	3.885
15	20	600	120	0.5	Brass-5	0.21494	9.02
16	30	200	40	0.5	Brass-6	0.7088	10.13
17	30	400	80	1	Copper-6	0.85779	7.515
18	30	600	120	0	Bronze-6	2.06321	6.1

4.1. -nD angle, MAOT and Information Divergence

Table 4 shows the values obtained for -nD angle, MAOT and ID methods by following the Equations (1), (3) and (5), respectively. All the values of experiments obtained the same values for the considered optimization methods. Here, the least value obtained is considered as the first rank. Therefore, the first rank was obtained for experiment number 14 having the input parameters as current (20 Amps), pulse-on (400 μs), pulse-off (80 μs), flushing pressure (0 bar), and the electrode of bronze material. Now, the results were to be compared with the MOORA method. MOORA gives similar results like this so it can be understood that -nD angle, MAOT and ID methods are easy to process with only one formula to obtain similar results as MOORA which is a five-step method.

Table 4. Closeness of -nD angle, MAOT, and ID.

Experiments	-nd Angle	Rank	ID	Rank	MAOT	Rank
1	0.523759	6	0.407744	6	0.203928316	6
2	0.649438	13	0.850006	13	0.514031557	13
3	0.724869	16	1.569646	16	1.040733572	16
4	0.306271	3	0.107085	3	0.032286807	3
5	0.733156	18	1.74672	18	1.168936543	18
6	0.641067	10	0.805553	10	0.481761682	10
7	0.616797	9	0.693726	9	0.401269021	9
8	0.385929	4	0.183075	4	0.068913022	4
9	0.600007	8	0.628096	8	0.354653269	8
10	0.555468	7	0.486952	7	0.256789623	7
11	0.645751	12	0.829998	12	0.499491453	12
12	0.719186	15	1.473113	15	0.97044709	15
13	0.20953	2	0.046984	2	0.009772648	2
14	0.187813	1	0.037327	1	0.006969425	1
15	0.731041	17	1.696185	17	1.132449399	17
16	0.685009	14	1.089674	14	0.689414919	14
17	0.641214	11	0.806301	11	0.482304034	11
18	0.428714	5	0.237302	5	0.098646616	5

4.2. Multi-Objective Optimization Based on Ratio Analysis (MOORA)

This optimization is used in electrical discharge machining since it can help in maximizing the desired benefits/outputs by minimizing the efforts/inputs request. Here, the MOORA multi-response optimization technique was used for comparing the results of newly introduced with these well-established methods. This method also has a weightage factor that can be provided to give more importance to certain parameters, but in this study, equal weightage was considered for all the parameters. Weightage factors are generally chosen according to the importance of different output parameters. To show the application and calculation of the weightage factor, here, it is taken the same weightage factor as 0.5 (equal weightage for two parameters) for each parameter. Optimized data values and final ranking are shown in Table 4. The response table also provides rank as per the most effective parameter. The highest value of each factor is taken as the optimum level for overall performance characteristics.

Table 5 represents the normalized values obtained by following Equation (7), and this helps to bring all the values in the range of [0, 1]. Then, the weighted values are normalized by considering the weightage of 0.5. The final step of calculation of overall performance was shown that helps to find out the optimum level. In this case, the optimum value was obtained for experiment number 14 having the input parameters as current (20 Amps), pulse-on (400 µs), pulse-off (80 µs), flushing pressure (0 bar), and the electrode of bronze material.

Table 5. Normalized decision and weighted matrices.

Experiments	Normalization of Decision Matrix		Normalized Weighted Matrix		YA
	MRR (gm)	Ra (µm)	MRR (gm)	Ra (µs)	
1	0.168974	0.149308	0.028162	0.024885	−3.78521
2	0.140156	0.275391	0.023359	0.045898	−8.16386
3	0.02849	0.197419	0.004748	0.032903	−6.34861
4	0.475156	0.205261	0.079193	0.03421	−3.5296
5	0.034712	0.332399	0.005785	0.0554	−10.7807
6	0.114942	0.209107	0.019157	0.034851	−6.14017
7	0.090054	0.134754	0.015009	0.022459	−3.84673
8	0.217766	0.117109	0.036294	0.019518	−2.38137
9	0.262924	0.350196	0.043821	0.058366	−9.79758
10	0.20565	0.211595	0.034275	0.035266	−5.59739
11	0.11939	0.226602	0.019898	0.037767	−6.68951
12	0.058616	0.341448	0.009769	0.056908	−10.9159
13	0.529843	0.181583	0.088307	0.030264	−2.36763
14	0.358904	0.117184	0.059817	0.019531	−1.41096
15	0.031181	0.272073	0.005197	0.045345	−8.80506
16	0.102824	0.305554	0.017137	0.050926	−9.4212
17	0.124438	0.226677	0.02074	0.037779	−6.65721
18	0.299306	0.183996	0.049884	0.030666	−4.03679

Figure 4 shows the graph comparing all the methods, i.e., -nD angle, Information Divergence, Multi-Angle Optimization Technique, and MOORA methods. From this figure, it can be observed that experiment numbers 2, 13, 14, and 17 have obtained the same results for all the methods whereas the former three methods have obtained the same results throughout the study. The first rank was given for experiment number 14 which is satisfying the optimum conditions. It could be observed that MRR is not the highest value here and SR is also not the lowest. In reality, experiment number 9 has the highest MRR and experiment number 8 has the lowest SR. In such situations, optimization techniques play a significant role.

To compare, relevant research carried out by other researchers is included here. Techniques such as Gray Relational Analysis [36], TOPSIS, Neural Network, Genetic Algorithm, Artificial Bee Colony Optimization, Finite Element Method, Simulated Annealing, Ant Colony Optimization Algorithm, Particle Swarm Optimization, Fuzzy-Optimization, and Sheep Flock Heredity Algorithm were implemented previously to optimize the electrical discharge parameters [37,38]. As few electrical discharge parameters exist, complex algorithms are not required for their optimization. They could be optimized by simple techniques as introduced in this study which provides similar results as the above mentioned [39].

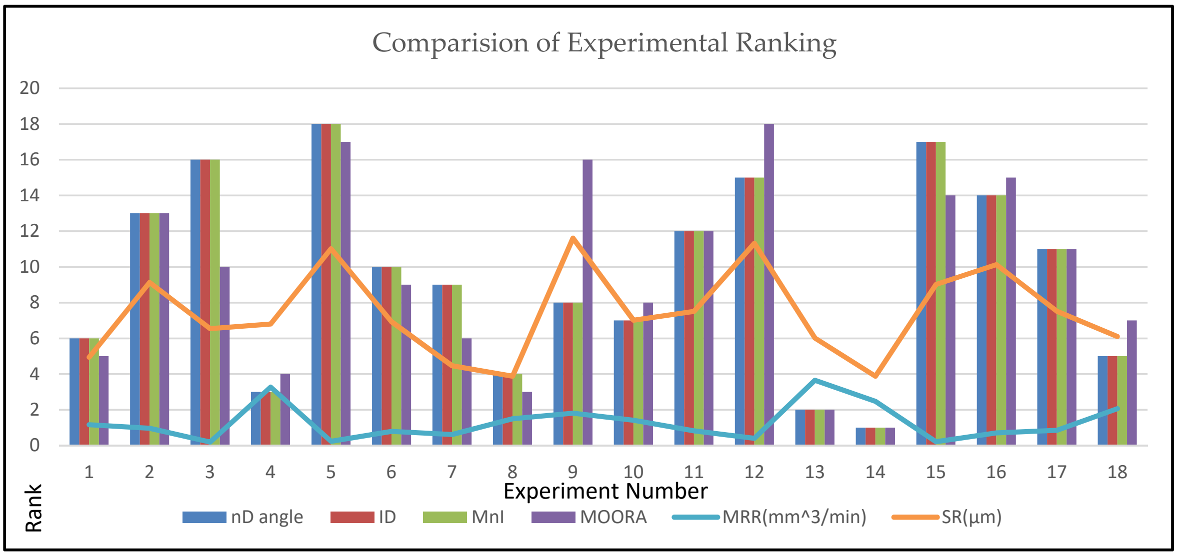

Figure 4. Comparison of optimization methods w.r.t. experimental ranking and output parameters.

5. Conclusions

In this study, optimization methods for Electrical Discharge Machining process parameters—current (Amps), pulse on time (µs), pulse off time (µs), flushing pressure (bar), and different electrodes measuring its output parameters (material removal rate and surface roughness)—have been compared to choose a simple technique for future implementation.

It was understood that techniques with a simple trigonometrical approach give the same results as the complicated optimization techniques which are popularly used in EDM machining for process parameters optimization. Among the experiments conducted using a different combination of input parameters, the input parameters of experiment number 14 were chosen as the optimum parameters (current 20 Amps, pulse-on 400 µs, pulse-off 80 µs, flushing pressure is zero, and bronze electrode) for obtained the condition of maximum material removal rate (2.47404 g) and minimum surface roughness (3.885 µm).

These techniques could also be extended for other applications such as in optimizing the process parameters in additive manufacturing for optimizing process parameters, in selecting wastewater treatment (optimum combination of parameters, the dosage of coagulants, catalysts in Advanced oxidation processes, etc.) in automobile and aerospace project management, etc.

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Nomenclature

Acronym/ Symbol	**Full Form/Unit**
EDM	Electrical Discharge Machine
MAOT	Multi-Angle Optimization Technique
MOORA	Multi-Objective Optimization based on Ratio Analysis
WBM	Weight before machining (grams)
WAM	Weight after machining (grams)
Pulse On and Off	µs
Current	Amps
MRR	Material Removal Rate (MM^3/Min)
SR(Ra)	Surface Roughness (Ra) µm
FP	Flushing Pressure (bar)

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